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# Modeling Residential Lawn Fertilization Practices: Integrating High Resolution Remote Sensing with Socioeconomic Data

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**Abstract** This article investigates how remotely sensed lawn characteristics, such as parcel lawn area and parcel lawn greenness, combined with household characteristics, can be used to predict household lawn fertilization practices on private residential lands. This study involves two watersheds, Glyndon and Baisman's Run, in Baltimore County, Maryland, USA. Parcel lawn area and lawn greenness were derived from high-resolution aerial imagery using an object-oriented classification approach. Four indicators of household characteristics, including lot size, square footage of the house, housing value, and housing age were obtained from a property database. Residential lawn care survey data combined with remotely sensed parcel lawn area and greenness data were used to estimate two measures of household lawn fertilization practices, household annual fertilizer nitrogen application amount (*N_yr*) and household annual fertilizer nitrogen application rate (*N_ha_yr*). Using multiple regression with multi-model inferential procedures, we found that a combination of parcel lawn area and parcel lawn greenness best predicts *N_yr*, whereas a combination of parcel lawn greenness and lot size best predicts variation in *N_ha_yr*. Our analyses show that household fertilization practices can be effectively predicted by remotely sensed lawn indices and household characteristics. This has significant implications for urban watershed managers and modelers.

**Keywords** Lawn fertilization · Lawn greenness · Remote sensing · Socioeconomic characteristics · Modeling · Object-oriented classification · LTER

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## Introduction

With the expansion of urban areas and residential development, turf grass has become a dominant land cover type in urban areas (Robbins and Birkenholtz 2003). It has been estimated that there are 10 to 16 million hectares of lawn in the continental United States, an area larger than that of some major U.S. crops like barley, cotton, and rice (Milesi and others 2005, Robbins and Birkenholtz 2003). On the one hand, urban residential lawns provide a variety of important benefits, such as aesthetic amenities (Jenkins 1994), carbon sequestration (Bandaranayake and others 2003), and mitigation of urban heat island effects (Spronken-Smith and others 2000). On the other hand, residential lawns may contribute significantly to water quality impairment through the application of lawn chemicals and fertilizers (Robbins and Birkenholtz 2003, Robbins and others 2001).

The impacts of lawn fertilizers as nonpoint pollutant sources on water quality have become increasing concerns in recent years (Law and others 2004, Overmyer and others 2005, Schueler 1995a, Schueler 1995b, Swann 1999). Before understanding how urban residential lawns and lawn fertilizer applications affect water quality, it is crucial to estimate the amount of fertilizer applied to urban watersheds from residential lawn care practices, and understand how household characteristics affect the rate of lawn fertilization application. Household surveys of lawn care practices are a valuable tool towards this end, but their effectiveness is limited by their relatively high costs (Law and others 2004, Swann, 1999). This problem, however, may be solved by modeling household lawn fertilization practices using household characteristics and remote sensing data, which can provide spatially distributed information over large watershed areas.

Remote sensing has a tremendous advantage in predicting lawn care practices, as it can explicitly reveal spatial patterns of lawn fertilization over a large geographic area in a recurrent and consistent way. With the recent availability of high spatial resolution satellite and aerial imagery (e.g., QuickBird, IKONOS, and Emerge, etc.) and advances in digital image processing, detailed lawn information at the household level, such as parcel lawn greenness and lawn area can be obtained for a large extent of study area in a cost-effective way (Zhou and Troy in press, Zhou and others 2006). Lawn greenness is likely to be affected by households' lawn care practices, such as fertilizer application rates, and thus can reflect the differences in lawn fertilizer application rates. Moreover, household lawn fertilizer application rate may vary with parcel lawn area. We hypothesize that parcel lawn greenness and lawn area obtained from remotely sensed data would correlate with differences in household fertilizer application rates.

Lawns have long been considered as status symbols, reflecting the different types of neighborhoods to which people belong (Jenkins 1994). For this reason, lawn management choices, such as fertilization and watering, may vary greatly among landowners (Grove and others 2006, Law and others 2004). Researchers have found that nitrogen fertilizer application rates are related to socioeconomic factors such as income and education (Osmond and Hardy 2004, Robbins and others 2001), and housing value, as well as housing age (Law and others 2004). Therefore, we hypothesize that household characteristics, such as housing age, property value, lot size, and square footage of the house, would correlate with and predict variation in household fertilization practices. More importantly, we hypothesize that a combination of remotely sensed lawn indices and household characteristics provides a better prediction of household lawn fertilization practices than either would provide on their own.

The objectives of this study are to: (1) examine how remotely sensed lawn indices, such as lawn greenness and area, predict variation in household lawn fertilization practices, (2) examine the relationship between household characteristics and lawn fertilization practices, and (3) investigate the usefulness of lawn indices and household characteristics in predicting household lawn fertilization practices.

## Methods

### Study Areas

This study involves two watersheds, Glyndon and Baisman's Run, in Baltimore County, Maryland, USA (Fig. 1). Both are part of the Baltimore Ecosystem Study (BES) monitoring network within the Gwynns Falls and Gunpowder watersheds. The Baltimore Ecosystem Study is a Long Term Ecological Research (LTER) of the National Science Foundation. Table 1 presents the summary characteristics of land cover land use, demography, and housing development in the two study watersheds. The Glyndon watershed is a headwater catchment of the Gwynns Falls watershed, with an area of about 0.8 km$^2$ and is characterized by predominantly residential land use, with a mix of other urban and open space. It has experienced rapid suburbanization in recent years as agricultural and forested lands have been developed.

Baisman's Run is a part of the Gunpowder watershed, with an area of approximately 3.81 km$^2$. It is a forest-dominated suburban area, characterized by low density, large lot development on septic systems in the upper third of the watershed (Law and others 2004).

### Data Collection and Preprocessing

#### *Geospatial Data*

Geospatial data used in this study include high-resolution color-infrared digital aerial imagery, LIght Detection And Ranging (LIDAR) data, and parcel boundaries. The digital aerial imagery from Emerge Inc. was collected on October 15, 1999. The imagery is 3-band color-infrared, with green (510–600 nm), red (600–700 nm), and near-infrared bands (800–900 nm). Pixel size for the imagery is about 0.6 m. The LIDAR data used in this study were acquired in March 2002, with an average point spacing of approximately 1.3 m. A surface cover height model with 1-m spatial resolution was derived from the LIDAR data, which was used to help differentiate between trees and herbaceous vegetation (Zhou and Troy in press).

Property parcel boundaries used in this study were obtained in digital format from Baltimore County, as current of 2003. We created a new GIS layer by extracting those parcels where lawn fertilizer application data were available.

#### *Lawn Fertilizer Application Data*

Data on household lawn fertilization practices were obtained from a household survey data collected in 2001

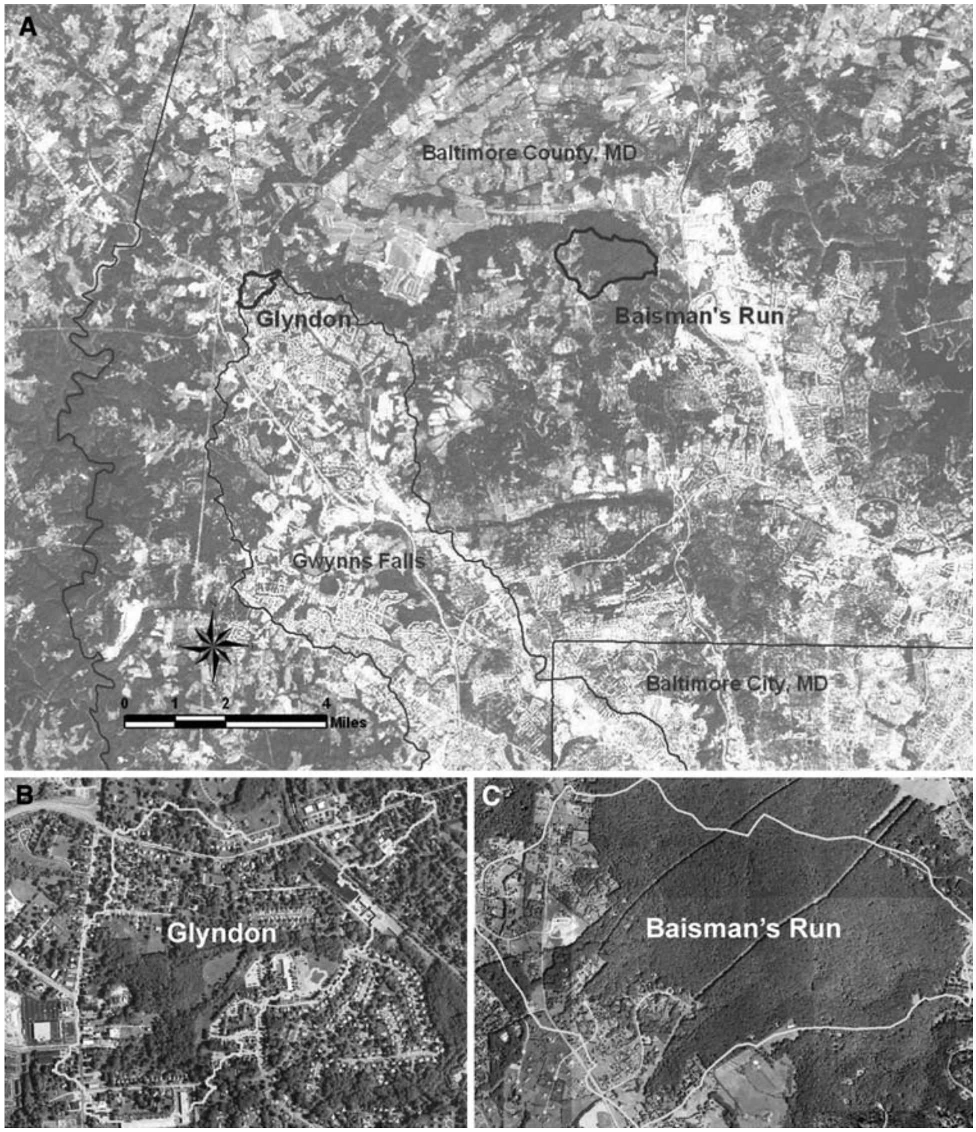


**Fig. 1** The Glyndon and Baisman's Run watersheds, located in Baltimore County, MD, USA

(Law and others 2004). This survey was designed to estimate household fertilizer application rates and water use practices for lawns in the two watersheds. Data were generated at the household level by a door-to-door survey. The two watersheds were partitioned into 10 subdivisions, with six in Glyndon and four in Baisman's Run. Nine of the subdivisions were single-family detached homes and one was a townhouse development. For each subdivision, 10 residential, homeowner-occupied households were randomly selected to participate in the survey. Seventy-three of the homeowners responded to the survey, among which 43 reported fertilizing their lawns. Most of the identified lawns were single-family detached homes ($n = 39$), with only four observations from townhouses.

In the survey, fifteen questions were designed to determine the annual amount of fertilizer the homeowners applied (Law 2003). For those homeowners who applied fertilizers by themselves, the respondents were asked to provide information on the frequency and amount of fertilizer used per application, in addition to the product name, but the specific type (e.g., N-P-K formulation) was not identified by the survey respondent. A commonly used fertilizer formulation (29N-3P-4K) was used to estimate the fertilizer $N$ application amount. The household annual fertilizer $N$ application amount was then estimated based on the type and amount of fertilizer product, and the frequency of application. For those homeowners who employed a professional lawn care service, a follow-up survey to the professional lawn care companies identified in the household survey was conducted to estimate the fertilizer $N$ application amount.

To reduce the possible errors caused by the self-reporting method, in the survey, different size bags of fertilizers were shown to respondents to help them identify the products they used, or the one that most closely resembled the size bag they used, and how much of the bag

**Table 1** Summary characteristics of land cover land use, demography and housing development in the study watersheds (partly adapted from Law and others (2004))

| | Glyndon | Baisman's Run |
|---|---|---|
| Watershed area (km$^2$) | 0.8 | 3.7 |
| Residential | 47% | 34% |
| Forest | 4% | 66% |
| Open urban space | 16% | 0 |
| Commercial, institutional | 32% | 0 |
| Percent lawn area | 15% | 25.5 & (75.5%)[a] |
| Population density (pers/ha) | 9.4 | 1(3.0) |
| Median yearly income ($) | 66,154 | 80,854 |
| Median household size (pers) | 3 | 2 |
| Median Age (yr) | 35–44 | 45–54 |
| Education attainment (Percentage of people 25 years and over with at least a college degree) | 43.0% | 59.0% |
| Ethnicity (Percentage of the population who are "white") | 87.3% | 87.7% |
| Housing density (house/ha) | 3.9 | 0.3(1.0) |
| Median of tax assessed market value of the house ($) | 163,264 | 365,810 |
| Average lot size (ha) | 0.13 | 0.93 |
| Average area of building footprint (m$^2$) | 150.2 | 302.6 |
| Median housing age (yr) | 37 | 19 |

[a] Values in parentheses refer to the residential portion of the Baisman's Run watershed and not the whole watershed

they used. The information provided by some of the respondents was further confirmed by revisiting those homeowners to check the product they used and the amount per application (Law, personal communication). The self-reporting method may lead to some bias (Law and others 2004). Further details about the survey data can be found in Law (2003) and Law and others (2004).

In this study, two indicators of household lawn fertilization practices were derived from the survey data, and used in later statistical analyses:

*N_yr*: estimated household annual application amount of nitrogen (Kg/yr). *N_yr* was obtained for each of the 43 individual lawns from the survey data.

*N_ha_yr*: household annual application rate of nitrogen (i.e., the application amount per unit lawn area) (Kg/ha/yr). *N_ha_yr* was measured by dividing household annual *N* application amount by parcel lawn area, which was derived from remotely sensed imagery and parcel data.

A large range was found for both the nitrogen application amount (*N_yr*) and the application rate (*N_ha_yr*) in the survey. A summary of *N_yr* and *N_ha_yr* is presented in Table 2.

**Table 2** Descriptive statistics of annual fertilizer N application amount and fertilizer N application rate

| Variables | *N* | Minimum | Maximum | Range | Mean | Std. Dev. |
|---|---|---|---|---|---|---|
| N_yr (kg/yr) | 43 | 0.40 | 211.29 | 210.89 | 23.61 | 37.91 |
| N_ha_yr (kg/ha/yr) | 43 | 10.51 | 369.68 | 359.17 | 97.57 | 88.28 |

### *Socio-economic Data*

For household characteristic measures, we used data from the Maryland Property View dataset (Assessments and Transaction database). Specifically, four indicators of household and property characteristics were used in this study: (1) lot size (*lotsize*), (2) size of building footprint (*housesize*), (3) housing value (tax assessed market value of the house) (*housevalue*), and (4) housing age (*houseage*).

### *Measuring Parcel Lawn Greenness and Lawn Area*

An object-oriented approach was used to measure the residential lawn greenness and lawn area at the parcel level (Baatz and Schape 2000, Benz and others 2004, Blaschke and Strobl 2001, DeFiniens Imaging 2004). Further details of these methods are documented in Zhou and others (2006) and Zhou and Troy (in press). We created a two-level hierarchical network of objects. In the lower level, we separated lawns from other land cover types; in the upper level, we summarized lawn greenness and lawn area by parcel.

We first segmented the image at a very fine scale, where object primitives were considered to be internally homogeneous, i.e., there was only one land cover class in each object primitive. However, a single real-world object, such as a lawn, generally was comprised of several object primitives due to spectral differences in different parts of each lawn. The segmentation of the image at the parcel level (the upper level) was created based on the thematic layer, i.e., the parcel boundary layer. Once the segmentations were done, a knowledge base of rules was created to perform the classification at the lower level to separate lawn primitives, i.e., segments of a lawn, from other land covers. Lawn primitives were differentiated as shaded and unshaded lawns. Other land covers classes included buildings, pavement, coarse vegetation (trees and shrubs), and bare soil (Zhou and Troy in press). A classification-based segmentation was then performed to merge the spatially adjacent lawn segments in each parcel into a larger object, that is, a lawn.

Lawn greenness and lawn area were summarized by parcel at the upper level. As lawn greenness information was blurred by shading for those shaded lawn areas, we measured parcel lawn greenness by only using unshaded portions of a lawn. But when calculating lawn area for each parcel, both the shaded and unshaded portions of a lawn were included. Moreover, we assumed in a residential parcel, the ground under tree canopy that cannot be sensed directly by remote sensing was covered by grass, and thus were also counted as parcel lawn area. In other words, the coverage area of tree canopy was also included in the total parcel lawn area. A comparison between the values of parcel lawn areas obtained from remotely sensed data with those measured during the survey indicated the validity of our assumption. Parcels were exported in vector format as polygons with attached attributes of lawn greenness and lawn area, which were used in later statistical analyses.

The Normalized Difference of Vegetation Index (NDVI), which has been widely adopted and applied to estimate vegetation productivity (Ricotta and others 1999), vegetation biomass (Liang and others 2005), and pasture growth rate (Hill and others 2004), was used to measure lawn greenness in this study. A considerable amount of research has demonstrated that NDVI is sufficiently stable to permit meaningful comparisons of seasonal and inter-annual changes in vegetation growth and activity because the ratioing of NDVI reduces many forms of multiplicative noises present in multiple bands of multiple-date imagery (DeFries and others 1999, Jensen 2000).

In a lawn, a typical healthy green grass blade reflects substantial amounts of near-infrared energy (ranging from 700–1200 nm) while absorbing much of the incident red wavelength energy for photosynthesis (Jensen 2000). The Normalized Difference of Vegetation Index, which is derived from reflectance in the red and near-infrared wavebands, provides a standardized method of comparing vegetation greenness between remotely sensed images. The formula of NDVI is given by:

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (1)$$

where $NIR$ is the reflectance in the near-infrared waveband, and $RED$ is that of the red waveband. The


**Fig. 2** Parcel lawns are extracted from high-resolution imagery, and classified by lawn greenness measured by mean NDVI

Normalized Difference of Vegetation Index value ranges from -1 to 1, but typically between 0.1 and 0.7 for vegetation. Higher index values are associated with higher levels of healthy vegetation cover, and higher possible density of vegetation (Jensen 2000).

Specifically, we used mean, standard deviation, and range of lawn NDVI as indicators of parcel lawn greenness. We used mean NDVI to measure the level of lawn greenness, while the standard deviation and range of NDVI as measures of the homogeneity of lawn greenness. Each of the 43 identified parcels was assigned a mean, standard deviation, and range of NDVI, as well as the total area of lawn. Figure 2 shows parcel lawns extracted from high-resolution imagery and classified by lawn greenness measured by mean NDVI.

## Statistical Analyses

We used multiple-linear regression to determine which combination of variables best predicts variance in each of the two lawn fertilization indicators, measured at the parcel level: (1) logarithmically transformed household annual $N$ application amount (*logN_yr*), and (2) logarithmically transformed household $N$ application rate (*logN_ha_yr*). Response variables were log transformed because a quantile-by-quantile (Q-Q) plot for each of the two untransformed indicators (i.e., *N_yr* and *N_ha_yr*) revealed a departure from normality (Fig. 3). A Q-Q plot draws the quantiles of a variable's distribution against the quantiles of a test distribution, in this case, the normal distribution, and forms a 45-degree line when the observed values of the variable are in conformity with normality. Explanatory variables included parcel lawn area, lawn greenness and household characteristics. A bivariate scatter plot also suggested that the relationship between *logN_yr* and lawn area might be better described by an exponential function

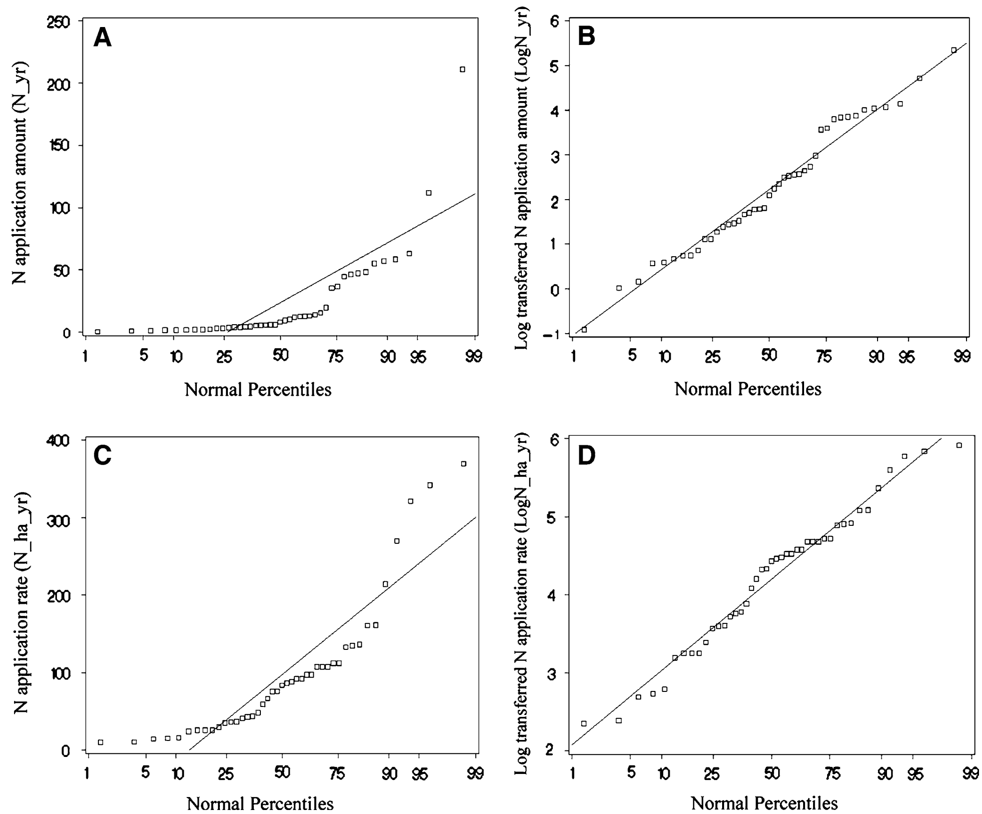


**Fig. 3** (**A**) Q-Q plots for annual fertilizer *N* application amount (*N_yr*), (**B**) logarithmically transformed annual fertilizer *N* application amount (*LogN_yr*), (**C**) annual fertilizer *N* application rate (*N_ha_yr*), and (**D**) logarithmically transformed annual fertilizer *N* application rate (*LogN_ha_yr*). The Q-Q plot for each of the two untransformed indicators (i.e., *N_yr* and *N_ha_yr*) revealed a departure from normality (**A** and **C**), whereas the logarithmically transformed variables closely follow a normal distribution (**B** and **D**)

rather than a linear one, as shown in Fig. 4. Table 3 lists the description, mean, and standard deviation for each variable.

We first examined how lawn area, lawn greenness, and household characteristics could be used to predict lawn fertilization practices, respectively. We then investigated whether a combination of lawn area, lawn greenness, and household characteristics could yield better predictions.

We used multi-model inferential procedures (Burnham and Anderson 2002) to determine which of those variables or some combinations best explain the variation in each of the two response variables. This procedure, which is based on minimization of Akaike's Information Criterion (AIC) (Akaike 1973, Akaike 1978), chooses the "best" out of a series of models by finding the model that strikes the best balance between model fit and model parsimony. More specifically, it selects the model that best explains the data with the fewest parameters. In this study, we used the adjusted AIC considering the relatively small ratio of the number of observations to the free parameters (Burnham and Anderson 2002, Wagenmakers and Farrell 2004). We also calculated the Akaike weight for each model, or the probability of a given model being the best one among a number of candidate models. Akaike weights are especially useful when the difference of AIC values between two models is small (Burnham and Anderson, 2002, Wagenmakers and Farrell 2004). Separate comparisons were run for each response variable.

## Results

Eight models were developed and compared for each response variable, yielding 16 models (Tables 4 and 5). We present the model parameters for all the predictors, as well as the significance levels. We also provide the $r^2$ value, AIC value, and Akaike weight for each model. For all models within each model group (i.e., the same response variable), we rank each model on the basis of its AIC value. The results are listed in Tables 4 and 5.

In the model group for annual *N* application amount, FA3 is the best model (table 4), which is given by:

$$\begin{aligned}\mathrm{logN\_yr} &= -4.681 + 0.730 * \mathrm{logLA} \\ &\quad + 4.898 * \mathrm{NDVI\_mean}\end{aligned} \quad (2)$$

where approximately 72% of variation in annual *N* application amount was explained jointly by logarithmically transformed lawn area (*LogLA*), and lawn greenness (*NDVI_mean*), with the most variation explained by *LogLA*. Both coefficients of *LogLA* and *NDVI_mean* were positive, with *LogLA* significant at the 99% confidence level, and *NDVI_mean* at the 95% confidence level (see table 4).

*LogLA* is the most significant variable in predicting *logN_yr*, accounting for about 68% of the variation (model FA1). The model with *LogLA* alone (FA1) was better than any of the other models without *LogLA* (e.g., FA2 and

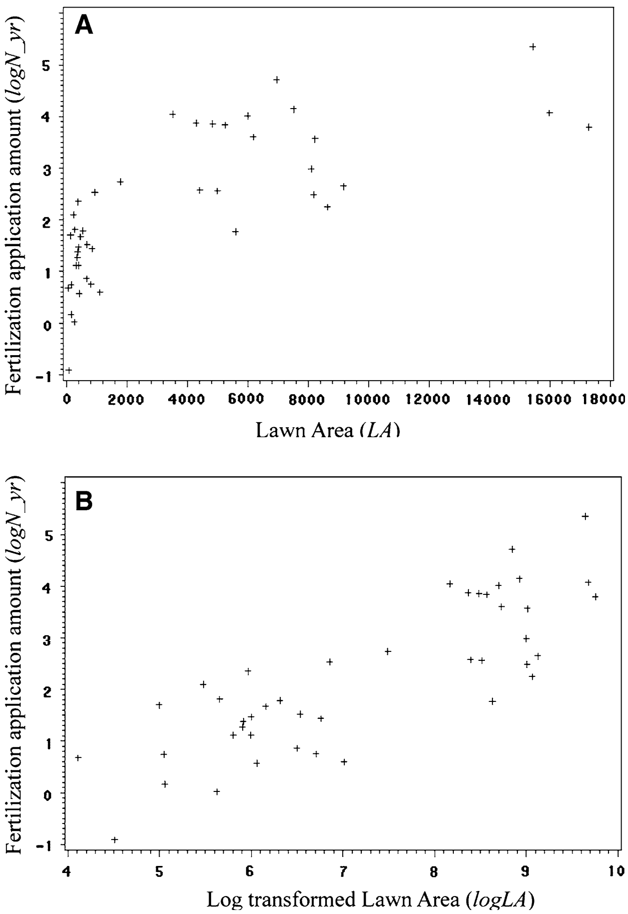


**Fig. 4** (**A**) The bivariate scatter plot suggests that the relationship between logarithmically transformed annual fertilizer *N* application amount (*logN_yr*) and lawn area might be better described by an exponential function rather than a linear one. (**B**) A linear relationship between *logN_yr* and the log transformed lawn area (*logLA*)

FA5), suggesting the importance of that variable in predicting annual *N* application amount.

*NDVI_mean* was not significantly correlated with *logN_yr* in the absence of other variables (model FA2). However, when controlling for the effect of parcel lawn area (*logLA*), there was a significantly positive relationship between *NDVI_mean* and *logN_yr* (model FA3). The Akaike weights show model FA3 is clearly superior to model FA1, suggesting the importance of *NDVI_mean* in predicting *logN_yr*.

Among the four indicators of household characteristics, only *housesize* and *housevalue* significantly explained variation in *logN_yr*, when controlling for the effects of the other three household characteristic variables (model FA4). The Akaike weights show no difference between model FA4, the one using all four indicators of household characteristics, and its simplified model, FA5, with only the two significant variables (i.e., *housesize* and *housevalue*) as predictors. The combination of the two variables (i.e., *housesize* and *housevalue*) could explain about 58% of variation in *logN_yr* (model FA5). When accounting for the effects of lawn area and lawn greenness, however, no household characteristics significantly explained the variation in *logN_yr* at the 95% significance level (model FA6, FA7, FA8).

For the models with *logN_ha_yr* as response variable (table 5), FH8 is the best model, which is given by:

$$\begin{aligned} \text{logN\_ha\_yr} &= 2.383 + 6.419 * \text{NDVI\_mean} \\ &\quad - 0.0000799 * \text{lotsize} \end{aligned} \tag{3}$$

where about 40% of variance in *logN_ha_yr* was explained by a combination of lawn greenness (*NDVI_mean*) and lot size (*lotsize*). However, the probability of FH8 being the best model is only 47% relative to 26% for the second best model (FH7), and to 21% for the third best (FH3), according to the Akaike weights. Therefore, while FH8 is clearly one of the three best models, AIC provides only relatively weak support for it being the best relative to FH7 and FH3. At the same time, the probability of FH7 being the best model is almost the same as that of FH3.

Both *LA* and *NDVI_mean* were significantly correlated with *logN_ha_yr*. Among the household variables, *lotsize* was the only one that significantly correlated with

**Table 3** Description and statistics of each variable

| Variables | Description | Mean | Std. Dev. |
|---|---|---|---|
| logN_yr[a] | Logarithmically transformed household annual application amount of nitrogen | 2.23 | 1.42 |
| logN_ha_yr[a] | Logarithmically transformed household annual application rate of nitrogen | 4.20 | 0.92 |
| LA[b]($m^2$) | Parcel lawn area | 3785.5 | 4589.0 |
| logLA[b] | Logarithmically transformed parcel lawn area | 7.24 | 1.62 |
| NDVI_mean[b] | Mean of lawn NDVI | 0.332 | 0.056 |
| Lotsize[b]($m^2$) | Lot size of the property | 4494.68 | 5093.16 |
| Housesize[b]($m^2$) | Size of building footprint | 194.68 | 49.42 |
| Housevalue[b]($) | Tax assessed market value of the house | 231,692 | 98,631 |
| Houseag[b](yr) | Built year of the house | 19.88 | 22.76 |

[a] Dependent variables

[b] Independent variables

**Table 4** Summary results for linear regression models predicting household annual *N* application amount

| Model | Explanatory variables/Parameter estimates (logN_ yr) | | | | | | Adjusted AIC | Rank | Akaike weight | $r^2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| FA1 | logLA | | | | | | 109.1 | 4 | 0.1102 | 0.6793 |
| | 0.725[a] | | | | | | | | | |
| FA2 | NDVI_mean | | | | | | 156.8 | 8 | 0.0000 | 0.0289 |
| | 4.313 | | | | | | | | | |
| FA3 | logLA | | | NDVI_mean | | | 106.2 | 1 | 0.4696 | 0.7165 |
| | 0.730[a] | | | 4.897[b] | | | | | | |
| FA4 | lotsize | housesize | | housevalue | houseage | | 122.7 | 6 | 0.0001 | 0.6327 |
| | 0.000063 | -0.00116[b] | | 1.35E-5[a] | 0.00918 | | | | | |
| FA5 | housesize | | | housevalue | | | 123.6 | 7 | 0.0001 | 0.5753 |
| | -0.00117[b] | | | 1.57E-5[a] | | | | | | |
| FA6 | logLA | NDVI_mean | lotsize | housesize | housevalue | houseage | 113.8 | 5 | 0.0105 | 0.7394 |
| | 0.669[a] | 3.522 | -2.2E-5 | -0.00056 | 4.94E-6 | -0.00247 | | | | |
| FA7 | LogLA | NDVI_mean | | housesize | housevalue | | 108.3 | 3 | 0.1643 | 0.7370 |
| | 0.587[a] | 3.762[c] | | -0.000579 | 5.3E-6[c] | | | | | |
| FA8 | LogLA | | NDVI_mean | | housevalue | | 107.5 | 2 | 0.2452 | 0.7250 |
| | 0.624[a] | | 4.688[b] | | 2.19E-6 | | | | | |

[a] significant at the 99% confidence level

[b] significant at the 95% confidence level

[c] significant at the 90% confidence level

**Table 5** Summary results for linear regression models predicting household annual average N application rate

| Model | Explanatory variables/Parameter estimates (logN_ha_yr) | | | | | | Adjusted AIC | Rank | Akaike weight | $r^2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| FH1 | LA | | | | | | 98.6 | 7 | 0.0078 | 0.2170 |
| | -0.0000940[a] | | | | | | | | | |
| FH2 | NDVI_mean | | | | | | 99.3 | 8 | 0.0055 | 0.2022 |
| | 7.335[a] | | | | | | | | | |
| FH3 | LA | | | NDVI_mean | | | 92.0 | 3 | 0.2109 | 0.3763 |
| | −0.00008476[b] | | | 6.554[a] | | | | | | |
| FH4 | lotsize | housesize | | housevalue | houseage | | 97.5 | 6 | 0.0135 | 0.3740 |
| | −0.0000997[b] | −0.000583 | | 3.24E-6 | -0.00863 | | | | | |
| FH5 | lotsize | | | | | | 97.0 | 5 | 0.0173 | 0.2472 |
| | −8.87E-5[a] | | | | | | | | | |
| FH6 | LA | NDVI_mean | lotsize | housesize | housevalue | houseage | 96.9 | 4 | 0.0182 | 0.4699 |
| | 0.00022 | 4.790[b] | 0.00027[c] | -0.00019 | −5.908E-7 | −0.00785 | | | | |
| FH7 | LA | | NDVI_mean | | lotsize | | 91.6 | 2 | 0.2576 | 0.4216 |
| | 0.000202 | | 6.254[a] | | -0.000256 | | | | | |
| FH8 | NDVI_mean | | | lotsize | | | 90.4 | 1 | 0.4693 | 0.3996 |
| | 6.419[a] | | | -0.0000799[a] | | | | | | |

[a] significant at the 99% confidence level

[b] significant at the 95% confidence level

[c] significant at the 90% confidence level

*logN_ha_yr* when controlling the effects of other variables of household characteristics (see model FH4). The AIC score of FH5, using *lotsize* alone, was very close to that of FH4 with all the four indicators of household characteristics in predicting *logN_ha_yr*.

Housing age did not significantly explain the variation in household fertilization practices, when accounting for the effects of several other variables. However, when plotting out the data of housing age and the logarithmically transformed annual *N* application rates (*logN_ha_yr*) (Fig. 5), a

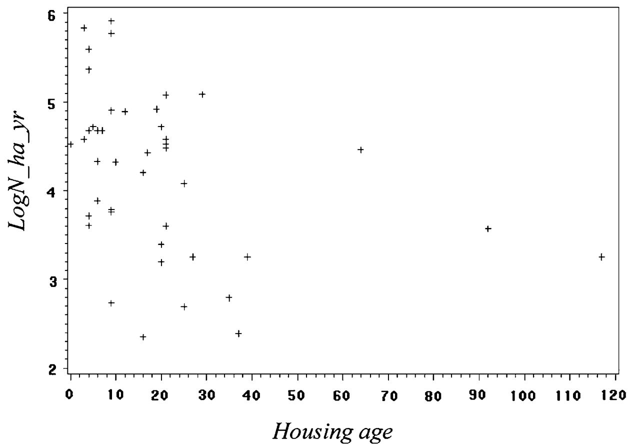


**Fig. 5** The scatter plot of the logarithmically transformed annual fertilizer $N$ application rate (*logN_ha_yr*) and housing age. A linear relationship is shown between those two variables, where the housing age was less than 50 years ($r^2 = 0.23$; $p = 0.0018$; $N = 40$)

linear relationship was clearly shown between those two variables, where the housing age was less than 50 years. In fact, a statistically significant negative relationship was found between housing age and logarithmically transformed annual $N$ application rates ($r^2 = 0.23$, $p = 0.0018$, $N = 40$), when only using data with housing age less than 50 years. When controlling for the effects of the other variables used in this study, but only using the observations with housing age less than 50 years, we found that housing age did not significantly explain variation in annual $N$ application amount (i.e., *logN_yr*). However, housing age was a very useful predictor for annual $N$ application rate (i.e., *logN_ha_yr*). The combination of housing age and lawn greenness best predicts annual $N$ application rate ($r^2 = 0.36$, $p = 0.0004$, $N = 40$).

## Discussion

### Theoretical Implications

The results from our analyses suggest that remotely sensed biophysical indices (i.e., lawn area and lawn greenness), combined with household characteristics, can be used to effectively predict household lawn fertilization practices. A combination of lawn area and lawn greenness is the best combination at predicting household annual $N$ application amount, whereas variation in household annual $N$ application rate is best explained jointly by lawn greenness and lot size.

Lawn area is the most significant predictor of household annual $N$ application amount. A power law relationship (i.e.,$y = \alpha x^{\beta}$), rather than a linear one, was found between lawn area and annual $N$ application amount. That is, there was a linear relationship between logarithmically transformed lawn area and logarithmically transformed annual $N$ application amount. The power of 0.725 (i.e., the coefficient of *logLA*, in model FA1), less than 1, indicates that landowners with bigger lawns would apply larger total amounts of fertilizer $N$ to their lawns, but with less per unit lawn area. This was also indicated in the significantly negative relationship between lawn area (*LA*) and $N$ application rates (FH1, table 5). Based upon our field observations of a number of these residences, we propose that this might be caused by the different lawn care practices directly around a homeowner's house relative to the remainder of the grass area (Fig. 6). In situations where homeowners have very large lawns, homeowners tend to intensively manage a lawn around their house: a primary lawn. The remainder of the property tends to be managed as tall grass or fields, which are mown only several times in the summer: secondary lawn. These field observations would be consistent with our results.

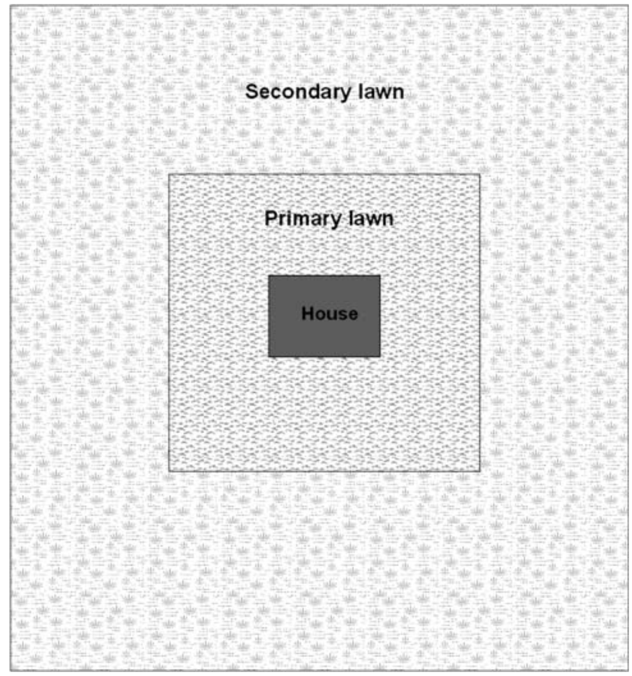


**Fig. 6** Primary lawn and secondary lawn

Lawn greenness is another useful predictor of household annual $N$ application amount. Our analyses indicated that adding the lawn greenness variable yielded better results in predicting $N$ application amount than when using lawn area alone (models FA3 and FA8). Both parameters of *NDVI_mean* in the best (FA8) and second best model (FA3) indicated a significantly positive relationship between lawn greenness and annual $N$ application amount, when controlling the effect of lawn area.

Household characteristics are useful predictors of household annual $N$ application amount. Among the household characteristics, housing value was the most significant one in predicting household annual $N$ application amount. The positive relationship indicates that higher $N$ application amounts are associated with houses of higher property values (model FA4). However, housing value was no longer significantly correlated with household annual $N$ application amount, when controlling the effect of lawn area (model FA8). This implies that the reason why landowners with higher property values tend to apply more fertilizers may be because they tend to have bigger lawns. In fact, there is no significant relationship between housing value and annual $N$ application rate (model FH4).

For household annual $N$ application rate, lawn greenness is the most significant predictor and was the only variable that significantly explained the variation in annual $N$ application rate in all three of the models with high Akaike weights (i.e., FH8, FH7, and FH3). The relationship between lawn greenness and annual $N$ application rate was nonlinear. Lawn greenness alone could only reflect about 20% of variation in $N$ application rate. This may be partly because lawn greenness measured by NDVI is influenced by several environmental factors other than fertilization practices, such as soil type, lawn watering, and climate. To be able to capture more variation in annual $N$ application rate, more factors should be included. For instance, our analyses show that including the variable of lot size (FH8) or lawn area (FH3) could yield better results. In this study, we didn't include one of the very important ecological variables, soil type, because currently no soils data for the study areas are available at the appropriate scale. Future research will examine how lawn greenness can be used to predict lawn fertilization practices by controlling for the effect of soils.

Lot size is the only indicator of household characteristics that significantly explained the variation in $N$ application rate (model FH4). However, the negative relationship is relatively weak. A previous study using the same survey data found that there was no significant relationship between lot size and average $N$ fertilizer application rate, although this was at the subdivision level (Law and others 2004). The possible reasons for this inconsistency are worth being further explored.

Previous research at the subdivision level has found a negative linear relationship between median housing age and annual average $N$ application rate (Law and others 2004). Our analyses at the household level indicate there is a nonlinear relationship between housing age and $N$ application rate. A negative linear relationship was found between housing age and logarithmically transformed $N$ application rate, when the housing age is less than 50 years. This result is consistent with that of previous research (Law and others 2004) that landowners of recent constructions tend to apply higher rates of $N$ fertilizers to help establish lawns. Lawns around new housing are often characterized by a "founder's effect" (Grove and others 2006), where homeowners work to rapidly establish landscape features such as grass, shrubs, and trees. This flurry of landscaping activity is often accompanied by significant inputs of fertilizers and irrigation. In many cases, significant inputs of fertilizers are also needed to compensate for poor soil quality. As these landscape elements are established over time, fertilizer inputs decline. For housing age greater than 50 years, there were only three observations, thus more observations should be included before appropriate statistical inference can be made.

In this study, we tested three indicators to measure parcel lawn greenness, the mean, standard deviation, and range of NDVI, respectively, among which we found the first to be most useful predictor of household fertilization practices. As empirically derived NDVI data can be influenced by soil backgrounds and atmospheric conditions (Huete and Liu 1994, Qi and others 1995), it might be worthwhile to investigate the capacity of NDVI to predict lawn greenness and household fertilization practices over a larger extent in a multi-temporal way. Moreover, there are other remotely sensed vegetation indices that can also be used to measure lawn greenness, which we did not apply in this study. However, a comparison of the capacities of various vegetation indices would be valuable for appropriate index selection.

The object-oriented classification approach provided a convenient and useful method for fine scale measurements of parcel lawn area and lawn greenness. The methods used in this study show promise for measuring spatial patterns of lawns and lawn greenness over large urban watersheds, in turn for measuring lawn fertilization practices using high spatial resolution aerial and satellite imagery.

## Management Implications

Our analyses show that household fertilization practices can be effectively predicted by remotely sensed lawn indices and household characteristics. This has significant implications for urban watershed managers and modelers. Firstly, our results indicated that parcel lawn area was a very important predictor of household $N$ application amount. Including other indicators, such as lawn greenness, further improved our predictions of $N$ fertilizer application amount. Secondly, models developed in this study could potentially be used to predict nitrogen loads from residential lawn management over large urban watersheds using high spatial resolution aerial and satellite imagery and property data. This will allow for great advances in nonpoint source assessment and modeling for urbanized watersheds. Finally, this study provides a blueprint methodology for characterizing parcel level vegetation and the spatial patterns of household lawn fertilization practices.

This could prove to be very valuable for watershed managers in designing and targeting campaigns for local outreach in pollution reduction efforts.

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